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A Machine Learning Based Approach for Investigation of Dry and MQL Environments While Turning Stainless Steels

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ABSTRACT

Stainless steel has unique material properties that made these materials ideal in many areas such as in tanks and storage vessels for corrosive liquids, in the chemical and petrochemical industry, in steam boilers, in the paint industry, in food plants, in mining. Such types of materials require final operations (finish process) for precise dimensions and good surface quality. Machining is one of the most effective methods for shaping the long-lasting materials used in common area. This paper focuses on the machinability study of 316L steels in both experimental and machine learning based data evaluation approach. A series of turning experiments were conducted under dry and MQL environments with different cutting parameter (cutting Speed, feed rate and depth of cut) combinations. The outcomes of this study were cutting forces, cutting temperatures and energy consumption. Machine learning-based models (decision tree and prediction model) have predicted cutting force and cutting temperature with high accuracy in dry and MQL environments using cutting speed, feed rate, and depth of cut. The lower error values and higher R^2 coefficients obtained, particularly under MQL conditions, demonstrate the model's stability and effectiveness in machinability analysis. In the developed machine learning models, the R^2 value for cutting force reached 0.975, and for temperature it reached 0.957. RMSE values were obtained in the range of 4.03–4.87 and 2.76–3.32, respectively. Because the study combines both experimental and machine learning methods, it will be helpful for future research in machinability experiments.

Keywords: *Stainless steel, Cutting Environments, Machine Learning, AISI 316L, MQL*

Paslanmaz Çeliklerin Işlenmesi Sırasında Kuru ve MQL Ortamlarının Incelenmesi Için Makine Öğrenimine Dayalı Bir Yaklaşım

ÖZET

Paslanmaz çelik, aşındırıcı sıvılar için tanklar ve depolama kapları, kimya ve petrokimya endüstrisi, buhar kazanları, boya endüstrisi, gıda tesisleri ve madencilik gibi birçok alanda ideal kılan benzersiz malzeme özelliklerine sahiptir. Bu tür malzemeler, hassas boyutlar ve iyi yüzey kalitesi için son işlemlere (bitirme işlemleri) ihtiyaç duyar. Talaşlı imalat, yaygın olarak kullanılan uzun ömürlü malzemelerin şekillendirilmesinde en etkili yöntemlerden biridir. Bu makale hem deneysel hem de makine öğrenimi tabanlı veri değerlendirme yaklaşımıyla 316L çeliklerinin işlenebilirlik çalışmasına odaklanmaktadır. Farklı kesme parametre kombinasyonlarıyla (kesme hızı, ilerleme hızı ve talaş derinliği) kuru ve MMY ortamlarında bir dizi tornalama deneyi yapılmıştır. Bu çalışmanın sonuçları kesme kuvvetleri, kesme sıcaklıkları ve enerji tüketimidir. Makine öğrenimi tabanlı modeller (karar ağacı ve tahmin modeli), kesme hızı, ilerleme hızı ve kesme derinliği kullanılarak kuru ve MMY ortamlarında kesme kuvvetini ve kesme sıcaklığını yüksek doğrulukla tahmin etmiştir. Özellikle MMY koşullarında elde edilen daha düşük hata değerleri ve daha yüksek R^2 katsayıları, modelin işlenebilirlik analizindeki kararlılığını ve etkinliğini göstermektedir. Geliştirilen makine öğrenimi modellerinde, kesme kuvveti için R^2 değeri 0,975'e, sıcaklık için ise 0,957'ye ulaştı. RMSE değerleri sırasıyla 4,03–4,87 ve 2,76–3,32 aralığında elde edildi. Çalışma hem deneysel hemde makine öğrenmesini bir arada bulundurması nedeniyle işlenebilirlik deneylerinde gelecekte yapılacak araştırmalar için yardımcı olacaktır.

Anahtar Kelimeler*: Paslanmaz çelik, Kesme koşulları, Makine öğrenmesi, AISI 316L, MMY*

1. INTRODUCTION

316L is a widely used low-carbon stainless steel. Its difference from 316-grade steel is its lower carbon content. However, the two materials are quite similar in terms of chemical composition. On the other hand, it contains more molybdenum and nickel and has a lower carbon content than 304-grade stainless steel. One of the notable characteristics of this steel is its high corrosion resistance, especially in environments like seawater. This type of material is ideal for resisting corrosion caused by high temperatures in welded joints. It's worth noting that it has lower machinability compared to its weldability and corrosion resistance [1].

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Various methods, such as casting or additive manufacturing, are used during the initial manufacturing phase of a material or a machine component. These processes are generally considered rough, and depending on the type of manufacturing, residue is deposited on the material. These residues do not reflect the material's true geometry, cause dimensional variability, and compromise the material's surface quality. Precision manufacturing processes are required to remove such residue from the material surface and achieve true dimensions. Machining is the most well-known and widely used of these processes [2–7]. From another perspective, machining plays a complementary role to the initial manufacturing processes. These processes can be performed on both computer-controlled and conventional machines. While computer-controlled machines offer much more flexibility in the mounting and use of cutting tools and parts, this is managed entirely manually on conventional machines. Another key difference is the variety of cutting parameters, which computer-controlled machines offer virtually infinite options in this regard. However, conventional machines have a more limited range of applications. In both cases, machining is widely used in today's technology.

The literature about the machinability of AISI 316L steels are given. Szczotkarz et al. analyzed the machinability of 316L stainless steel, which is frequently used in areas such as automotive manufacturing, aerospace aviation, and marine, under different lubrication and cooling conditions[8]. Natesh et al. investigated the tribological and surface morphology properties of 316L stainless steel during turning to investigate the effect of cutting fluids on machinability parameters [9]. Şirin and Şirin tested a hybrid method of pure minimum quantity lubrication, liquid nitrogen, and a combination of minimum quantity lubrication and liquid nitrogen to measure the machinability of stainless steel material under environmentally friendly machining conditions [10].

Korkmaz et al. performed some tribological tests, used 100Cr6 material against stainless steel material and performed wear tests under different lubrication and cooling conditions[11]. Danish et al. investigated the processing of stainless steel material produced by additive manufacturing under different lubrication and cooling conditions [12]. Korkmaz et al. conducted experiments under different lubrication conditions to determine the wear and friction characteristics of stainless steel using machine learning methods[13]. Ukamanal et al. investigated the effects of dry and cooled environments on turning of stainless steel [14]. Abbas et al. investigated the effects of different cooling conditions and changing process parameters during milling in their collaborative study on AISI 316 alloy [15]. Based on the results obtained from the literature review, the use of lubricants is of great importance in the machining of stainless steel. The use of lubricants results in significant improvements both on the surface of the material and in other machinability outcomes.

The figure below shows some input parameters used in machining. Different cutting tools and materials are preferred depending on the manufacturing method. There are many input parameters that can be adjusted by the machine, such as various cutting speeds and feed rates, and can be varied by changing the application of dry or oil-air based cooling. While changing the manufacturing method itself affects the entire process, special processes such as using materials with different hardnesses, high-speed machining, using materials whose properties have been altered by heat treatment, high-feed machining, machining with very high cooling properties, and machining with specially coated tools are also common.

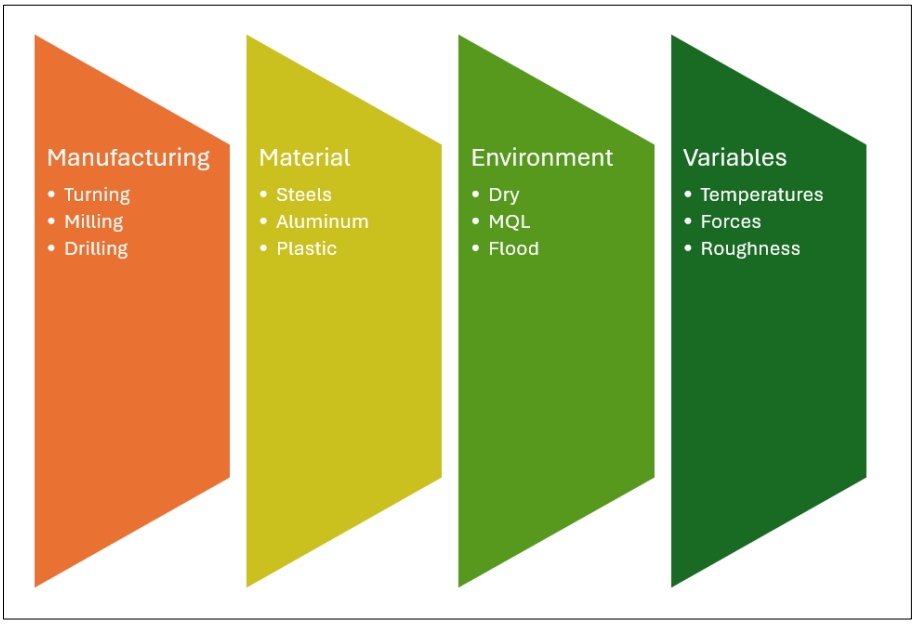


Figure 1. Some of the parameters used in the machining

It is crucial to examine lubricant use in experimental settings and to test it under different cutting parameters to understand its sustainability. The main objective of this study is to comparatively analyze the machinability performance of AISI 316L stainless steel in dry and MQL environments using experimental and machine learning-based approaches. Existing studies in literature are generally either experimental or modeling-based, and studies that evaluate these two approaches together are limited. In this respect, the study aims to fill the gap in literature.

2. MATERIAL AND METHOD

2.1. Work material, cutting tools and machine tool

AISI316L stainless steel was used in the experiments. The material is widely used in industry, and its inclusion in this study was primarily due to its less academic research compared to other stainless steels. Cutting tools with code CCMT-09T308-304 were selected for the experiments in this study. A new cutting tool was used in each experiment to obtain more accurate data and eliminate wear-related problems. The workpiece used in the experiments had a diameter of 100 mm, and the total machining length for each operation was set at 200 mm. These dimensions were chosen to ensure stable conditions during the cutting process and to improve the repeatability of measurements. The chemical composition of AISI 316L material contains approximately 16–18% Cr, 1% Si, 2% Mn, 10–14% Ni, and 2–3% Mo. Its tensile strength is approximately 485 MPa and its hardness is around 22 HRC.

A conventional lathe was selected for the experiments, and adjustments were made prior to the experiments. A photograph of the lathe is shown below. A dynamometer was adapted to the lathe for the experiments and served as a tool holder. A temperature sensor, manufactured by the same company as the dynamometer, was also adapted to the lathe and measures the cutting edge using a radiation beam focused on the cutting edge. Because high cutting forces are generated during cutting, and most heat is concentrated in this area, both sensors provide highly efficient result. The appearance of the experimental setup during the process is given in Figure 2.



Figure 2. Experimental setup.

2.2. Experiments and sensors

The experiments were conducted at a constant depth of cut (0.3 mm) using three different feed rates (0.1 mm/rev, 0.2 mm/rev, and 0.3 mm/rev) and three different cutting speeds (120 m/min, 180 m/min, and 240 m/min) while varying the basic turning parameters. To avoid any problems during the experiments, preliminary experiments were conducted to remove residual slag. Furthermore, preliminary experiments were conducted to determine the range of cutting parameters. The primary objective here was to prevent uncontrolled chip formation or excessive vibration.

In this study, experiments were conducted in two different cutting environments. This section discusses the properties of cutting fluids applied during turning. Dry machining is one of the oldest manufacturing methods

and can be performed without any preparation or additional materials. However, for the other machining method, minimum quantity lubrication, a plant-based lubricant was used. The MQL oil used is plant-based and is an environmentally friendly cutting fluid with low viscosity. The nozzle used to spray the minimum quantity of oil was directed at the point of contact between the cutting tool and the material at a 30-degree angle and a pressure of 6 bar. The distance from the nozzle to the cutting environment was set at 100 mm.

Three separate sensors were used in the experiments. One of these sensors is a dynamometer and serves as a tool holder for the cutting tool. The cutting tool, which moves with the carriage, both performs the cutting process and measures the force values. Another sensor, a temperature sensor, views the cutting environment from above and measures the radiation properties. Both sensors can take real-time measurements and transmit data to a computer via a cable. Additionally, the energy consumed during turning under selected cutting parameters and different cutting conditions were measured. For this purpose, a KAEL Multiser 02 PC TFT Network Analyzer was used to measure energy consumption.

2.3. Data evaluation

During the experimental studies, cutting parameters such as cutting speed, feed rate, and depth of cut were determined and applied separately for each condition. The cutting forces generated during the process were measured with a dynamometer, and temperature values were recorded using appropriate temperature sensors. The obtained force and temperature data were then preprocessed for machine learning methods. First, the effects of the input parameters on force and temperature were modeled using a decision tree algorithm. Then, the random forest method was applied to provide higher accuracy and generalization capability. The performance evaluation of the models was carried out through error rates and accurate values. Thus, the machinability of AISI 316L steel under dry and MQL conditions was analyzed not only with experimental observations but also with artificial intelligence-supported prediction methods.

3. RESULT AND DISCUSSION

3.1. Cutting forces

The graph below shows the changes in cutting force depending on feed and cutting speed. Furthermore, as can be seen in the graph's columns, the cutting forces generated in dry and minimum quantity lubrication environments are shown. As can be seen from the graph, a general decrease in cutting forces is observed with increasing speed, while the other two are constant. These results are consistent with similar studies reported in the literature. For example, studies by Demirpolat et al. [16] and Özlü et al. [17] showed that increasing the cutting speed reduced the cutting forces. This applies to both dry and minimum quantity lubrication environments. On the other hand, when we increase cutting speeds and hold the feed constant, we see an increase in cutting force. This change also applies to dry and minimum quantity lubrication environments. Looking at all the columns in the graph, the lowest cutting force occurs at a cutting speed of 240 m/min with a feed rate of 0.1 mm/rev. The lowest cutting force values were obtained in both dry and minimum quantity lubrication environments for these parameters. Therefore, this parameter can be selected as the optimum. Furthermore, it can be said that the highest cutting force values were obtained at the highest values of both feed and cutting speed. When comparing dry and minimum lubrication environments, minimum lubrication results in lower cutting forces under all conditions. This demonstrates the importance of lubrication in the machining of stainless steels, making it essential for both easier cutting and lower power consumption. According to the general assessment, the cutting force was reduced to a minimum level (55 N) at a feed rate of 0.1 mm/rev and a cutting speed of 240 m/min, while it reached maximum values (149 N) under conditions of 0.3 mm/rev and 240 m/min.

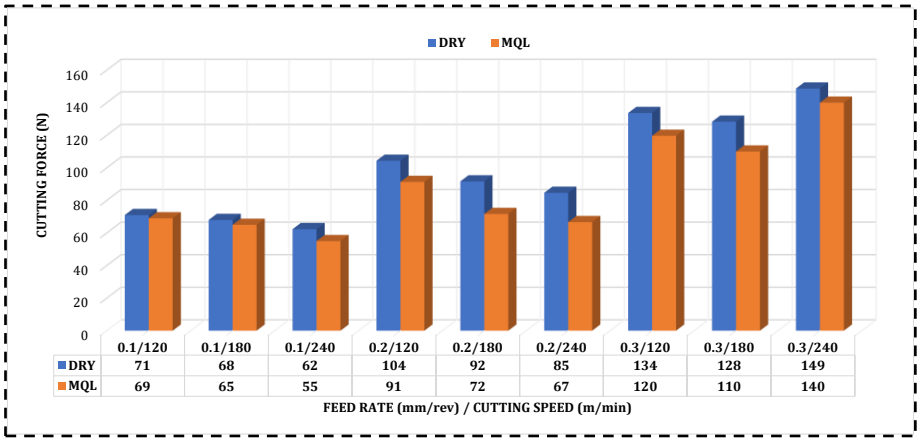


Figure 3. Cutting force change with parameters.

3.2. Cutting temperatures

The graph below shows the temperature at the cutting tool tip, depending on feed rate and cutting speed, in dry and minimally lubricated environments. With certain exceptions, temperatures are higher in dry environments than in minimally lubricated environments. This can be explained by the increased temperature due to the high frictional forces caused by the absence of any lubricant or coolant in the dry environment. Similarly, studies by Binali et al. [18], Salur et al.[19], and Aslan et al[20]. have also reported that the use of MQL significantly reduces shear temperatures. The exception here is the temperatures observed under cutting conditions of 0.3 mm/rev and 120 m/min. This can be explained by the insufficient access to the cutting zone tomorrow. However, looking at the general trend, it can be said that the use of lubricants in the machining of stainless steel makes a significant difference. As can be seen in this graph and the previous cutting force graphs, the use of lubricant in cutting not only reduces the required power consumption but also prevents tool wear by reducing temperatures. Considering the values in the graph, the highest cutting temperature occurs at 0.3 mm/rev and 240 m/min, i.e., the highest feed and cutting speeds. Conversely, considering the optimum cutting temperatures, it occurs at 0.1 mm/rev and 180 m/min, and this occurs in a lubricated environment. This graph demonstrates the importance of lubricant use and parameter selection in the machining of stainless steels. Cutting temperature values were measured at low parameters in the range of approximately 34–45 °C, while reaching levels of 86–92 °C under the highest conditions.

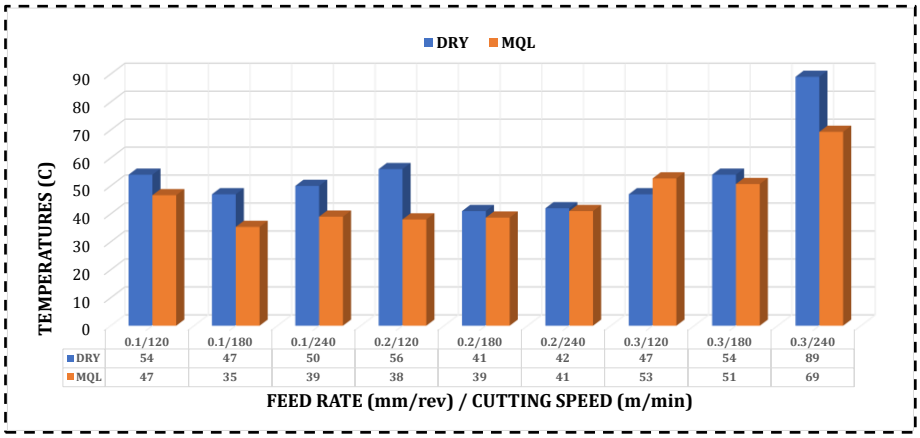


Figure 4. Cutting temperature changes with parameters.

3.3. Energy consumption

The graph below shows the energy consumption rates in stainless steel machining at different feed and cutting speeds, as well as in lubricated environments. Considering this graph, energy consumption decreases at lower feeding and cutting speed values. Similar observations have been reported in the literature, showing that higher cutting parameters lead to an increase in energy or power consumption [21,22]. Sivalingam et al. [23] and Korkmaz et al. [24] stated that the use of lubrication strategies increased energy efficiency by reducing friction and cutting resistance during machining processes. A general trend indicates that machining in a dry

environment always consumes more energy than with minimal lubrication. The highest energy consumption is observed at the highest feed and cutting speed values. Therefore, the importance of optimal data analysis and lubricant use in stainless steel machining should be emphasized to reduce energy consumption, which significantly impacts both total costs and carbon emissions. In general, energy consumption values were minimal at low parameters, while they increased significantly at high feed and cutting speeds.

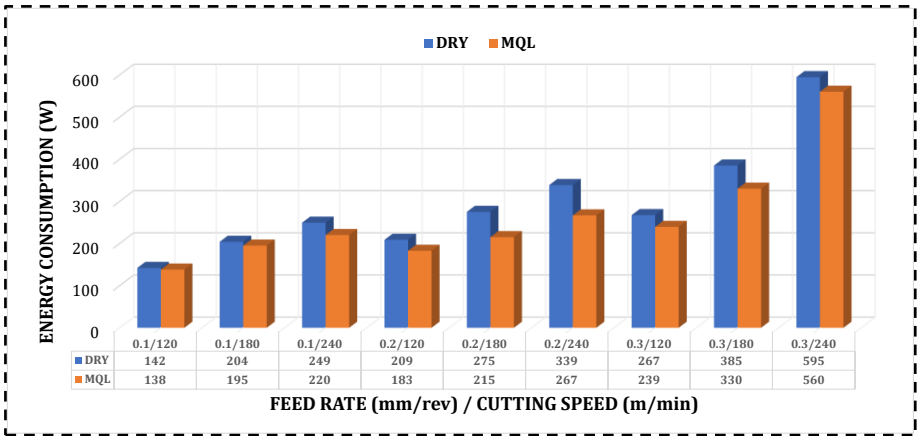


Figure 5. Energy consumption changes with parameters.

3.4. Machine learning

In traditional machining processes, cutting parameters such as cutting speed, feed rate, and depth of cut have a decisive effect on cutting forces and the temperature generated in the cutting zone. Especially in dry and MQL environments, the interaction of these parameters causes machinability indicators to exhibit nonlinear behavior. While it is difficult to fully model these complex relationships with classical statistical methods, machine learning-based approaches offer a powerful alternative in predicting multivariate and nonlinear systems [13,25,26]. In this study, cutting speed, feed rate, and depth of cut are considered as input parameters; cutting forces and temperature values are evaluated as output parameters. The aim is to predict machinability behavior with high accuracy in different lubrication environments using the developed machine learning models and to comparatively analyze process performance. Decision tree and forecasting analyses were conducted within this scope.

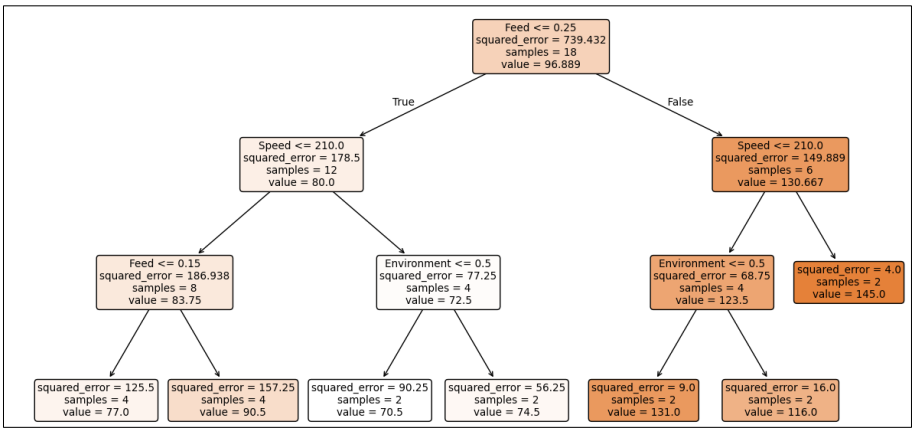


Figure 6. Decision tree model for cutting force.

When Figure 6 is examined, it is clearly seen that the most dominant parameter in the decision tree structure of cutting force is the feed rate. The fact that the feed rate plays a differentiating role at the root node of the tree shows that cutting forces are primarily dependent on the chip load. While cutting speed and environmental conditions stand out as secondary determinants at low feed rates, it has been observed that cutting speed and lubrication environment have a more significant effect on force values at high feed rates. In particular, the lower cutting forces observed in MQL environments and at high cutting speeds reveal that the lubrication and cooling effect improves machinability by reducing friction. Obtaining low error values at the leaf nodes shows that the decision tree provides a reliable and stable model for cutting force prediction.

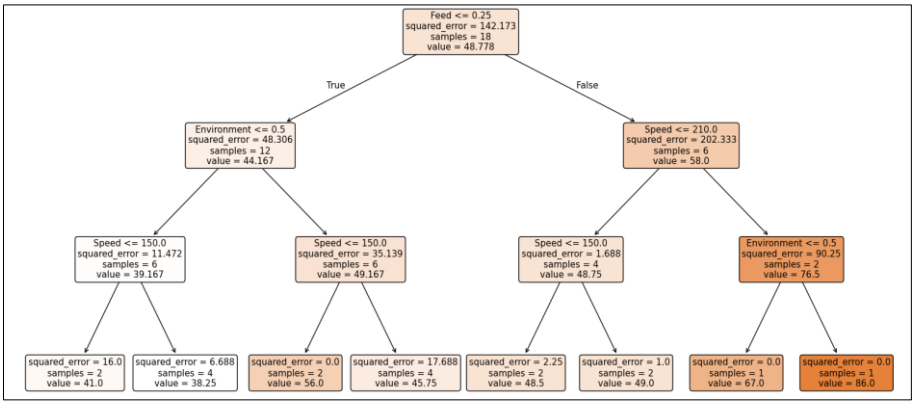


Figure 7. Decision tree model for Temperature.

Figure 7 shows that the decision tree results for cutting temperature reveal that the feed rate is again the primary distinguishing parameter, but the lubrication medium and cutting speed play a more dominant role in temperature generation. At low feed rates, environmental conditions are decisive in determining the temperature, and it is clearly seen that the MQL medium provides lower temperature values compared to dry cutting. At high feed rates, it was determined that the increase in cutting speed significantly increases the temperature, and this effect becomes more pronounced, especially under dry cutting conditions. Obtaining near-zero error values at some leaf nodes shows that the model offers high accuracy in temperature prediction and successfully represents parameter-output relationships. This confirms that the machine learning-based approach is an effective tool in modeling the thermal behavior in the cutting zone.

Table 1. Prediction model for cutting force.

F					
DRY					
1		2		3	
Experimental	Prediction	Experimental	Prediction	Experimental	Prediction
66	75.36	74	79.23	73	79.34
67	73.45	69	74.45	68	74.57
61	65.88	64	69.06	62	67.23
106	97.72	102	95.62	105	98.7
92	90.4	89	87.46	94	92.53
80	78.44	89	84.48	85	82.79
134	130.31	137	132.08	130	127.27
128	127.29	132	130.12	125	123.42
147	143.12	150	144.22	149	142.94
MQL					
1		2		3	
Experimental	Prediction	Experimental	Prediction	Experimental	Prediction
82	82.56	83	83.98	84	83.83
93	88.05	91	86.95	87	84.6
82	78.23	86	81.0	80	76.76
93	89.7	92	88.11	89	88.1188.03
71	78.62	67	73.75	77	81.12
67	70.08	65	69.48	68	72.33
120	120.49	118	118.55	121	120.14
112	117.01	108	115.14	110	115.39
143	137.43	137	132.41	140	137.47
MSE: 23.71		MSE:22.37		MSE:16.29	
RMSE:4.87		RMSE:4.73		RMSE:4.03	
MAE:4.14		MAE:4.34		MAE:3.47	
R2: 0.967		R2:0.968		R2:0.975	

When Table 1 is examined, comparing the experimental and predicted values of the shear force, it is seen that the developed machine learning model offers high prediction accuracy in both dry and MQL environments. The low MSE (16.29–23.71), RMSE (4.03–4.87), and MAE (3.47–4.34) values obtained for all iterations indicate that the model's error level is within acceptable limits. It is particularly noteworthy that the predicted force values in the MQL environment are closer to the experimental results, and the R^2 value increases to 0.975. This can be attributed to the more stable shear conditions and reduced friction effects in the MQL environment, allowing the model to learn parameter-output relationships more clearly. Overall, it can be said

that the shear force can be predicted with high accuracy using the machine learning method, and the model exhibits consistent performance across different experimental repetitions.

Table 2. Prediction model for cutting force.

T					
DRY					
1		2		3	
Experimental	Prediction	Experimental	Prediction	Experimental	Prediction
45	43.2	46	43.96	49	45.57
34	38.02	37	38.99	35	39.07
39	40.58	38	39.22	40	40.66
37	40.55	40	42.59	37	41.77
39	38.68	38	38.66	39	38.71
41	41.62	40	39.67	42	41.73
50	48.95	55	53.51	53	51.19
48	48.21	55	54.62	49	50.32
67	65.16	73	74.36	68	68.85
MQL					
1		2		3	
Experimental	Prediction	Experimental	Prediction	Experimental	Prediction
56	54.89	53	52.76	54	53.72
47	47.44	50	48.69	46	45.75
52	50.41	49	47.58	50	48.52
56	52.01	55	50.86	57	52.42
41	43.18	43	44.02	40	42.43
43	45.39	40	42.05	44	44.53
47	49.9	48	52.0	46	51.92
50	50.24	55	54.82	57	55.8
86	77.55	92	83.4	89	80.31
MSE: 8.31		MSE:7.62		MSE:11.05	
RMSE:2.88		RMSE:2.76		RMSE:3.32	
MAE:2.12		MAE:1.94		MAE:2.37	
R2: 0.941		R2:0.957		R2:0.929	

Table 2 shows that the results obtained for the cutting temperature demonstrate the success of the machine learning model in predicting thermal behavior. The fact that the calculated RMSE values for DRY and MQL environments range from 2.76 to 3.32, and the MAE values remain around 2°C, indicates that the model provides high accuracy in temperature prediction. In particular, the R^2 values in the MQL environment, ranging from 0.929 to 0.957, show that the lubrication and cooling effect makes temperature generation more predictable. Although prediction errors increase somewhat at higher temperature levels (especially in recent experiments), the overall trend is accurately captured. These results confirm that the machine learning approach can successfully model the complex heat generation mechanisms in the cutting zone and provide reliable predictions in different lubrication environments.

In addition to graphical evaluation, the predictive performance of the developed machine learning models was quantitatively assessed using statistical error measures. For shear force prediction, R^2 values reached up to 0.975, while RMSE values ranged from 4.03 to 4.87, and MAE values ranged from 3.47 to 4.34. Similarly, for shear temperature prediction, R^2 values ranged from 0.929 to 0.957, and RMSE values ranged from 2.76 to 3.32. These low error values and high coefficient of determination clearly demonstrate that the developed models provide reliable and accurate predictions for both output parameters. Overall, the effectiveness of machine learning models observed in this study is supported by previous research. Korkmaz et al. [27] demonstrated that machine learning algorithms can predict processing responses such as force and temperature with high accuracy. Similarly, Binali [25] and Kuntoğlu et al. [26] reported that AI-based models provide reliable predictions for processability indicators and can be used effectively for process optimization. The high R^2 values and low error metrics obtained in this study are in strong agreement with these findings.

4. CONCLUSIONS

In this study, the machinability of AISI 316L stainless steel in dry and MQL environments was analyzed using experimental and machine learning approaches. The results obtained from this paper are as follows:

- The lowest cutting force occurs at a cutting speed of 240 m/min with a feed rate of 0.1 mm/rev. The lowest cutting force values were obtained in both dry and minimum quantity lubrication environments for these parameters.

- The highest cutting temperature occurs at 0.3 mm/rev and 240 m/min, i.e., the highest feed and cutting speeds. Conversely, considering the optimum cutting temperatures, it occurs at 0.1 mm/rev and 180 m/min, and this occurs in a lubricated environment.
- The highest energy consumption is observed at the highest feed and cutting speed values.
- The developed machine learning model was able to predict both cutting force and cutting temperature with high accuracy using cutting speed, feed rate, depth of cut, and lubrication medium as input parameters; the high R^2 and low error metrics obtained in all experimental repetitions demonstrated the reliability and generalizability of the model.
- Lower error values and higher coefficients of determination obtained in the MQL environment have shown that the machinability behavior is more stable in this environment, and that machine learning-based models can be used as an effective tool in optimizing sustainable and efficient machining processes.

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